Santander, 14 May 2018

Bias adjustment of climate predictions in a climate service context

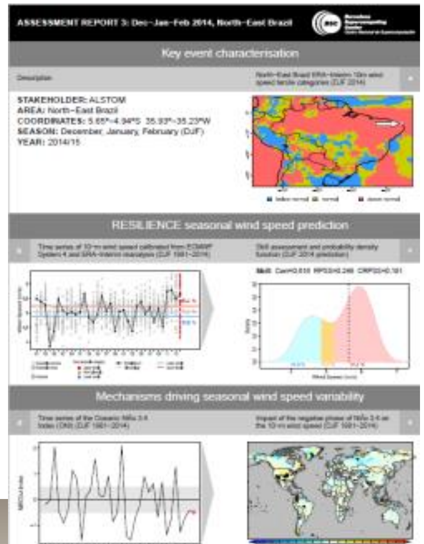
Francisco J. Doblas-Reyes

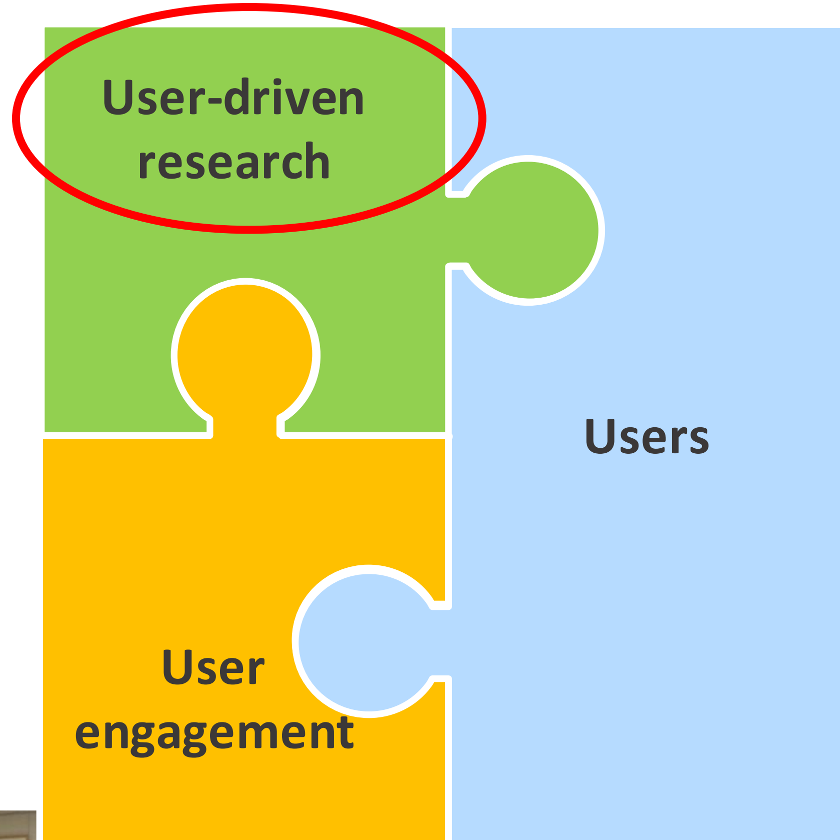
Outline

- **User engagement**
- **Climate prediction**
- **Different flavours of bias adjustment**
- **Expanding horizons: detection and attribution**
- **Reference uncertainty**
- **Need for forecast system improvement**

The climate services scene

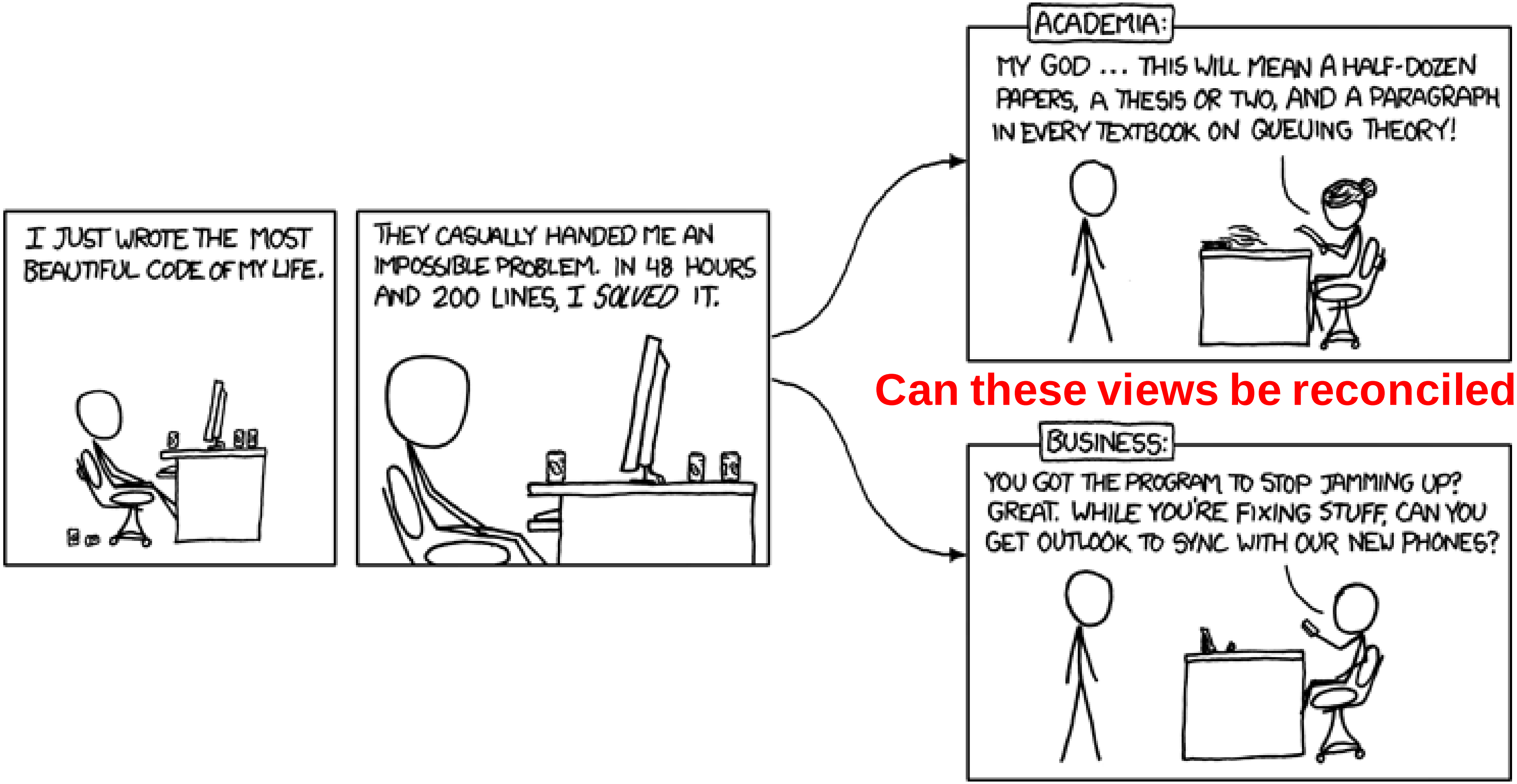
Case studies for specific needs





Participatory approaches

The intermediary dilemma

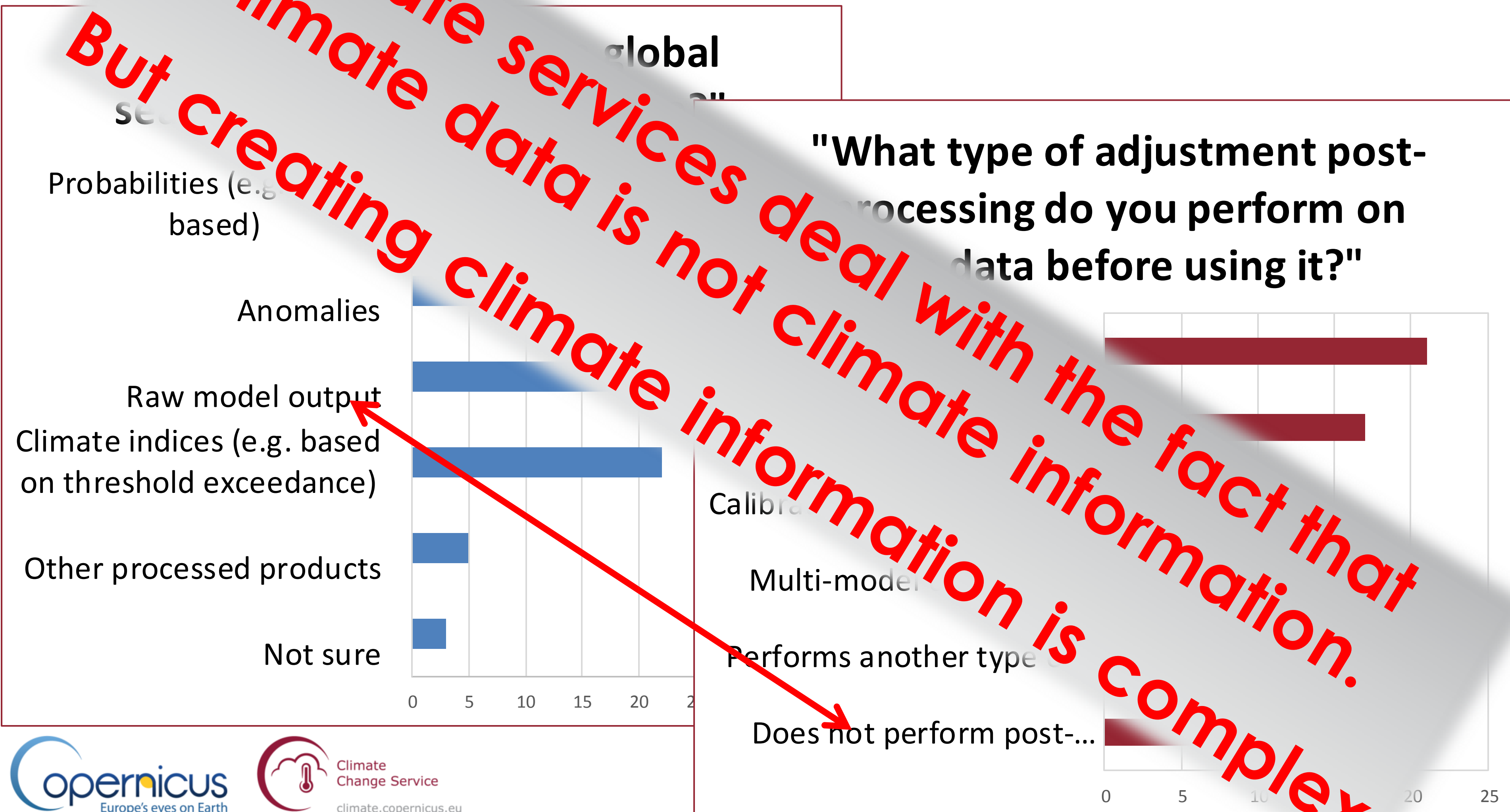


Can these views be reconciled?

xkcd.com

User engagement and consultation

Result[…] a user survey performed in the framework of the Cope[…] Change Service contract QA4Seas.



Climate services deal with the fact that climate data is not climate information.

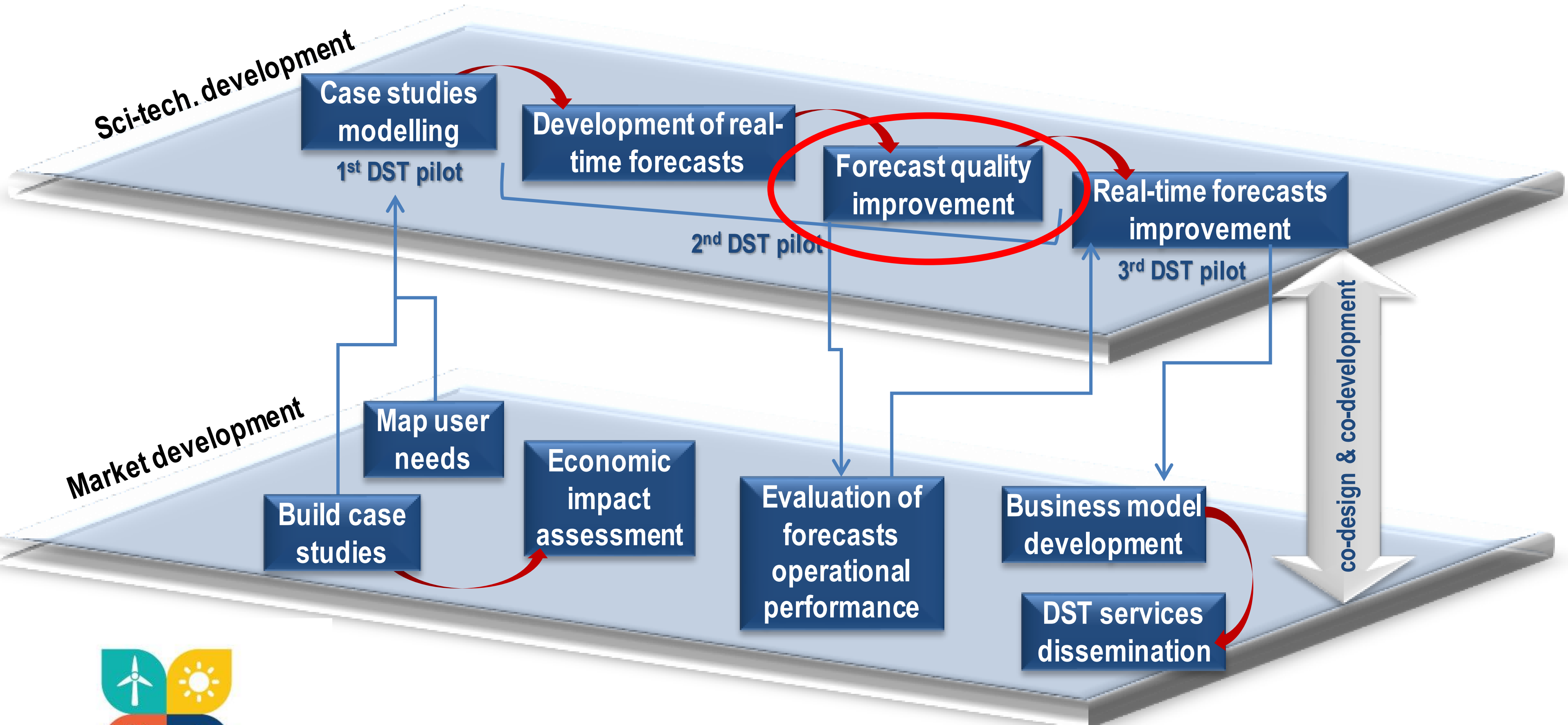
But creating climate information is complex

Copernicus Europe's eyes on Earth

Climate Change Service climate.copernicus.eu

M. Soares (Univ. Leeds)

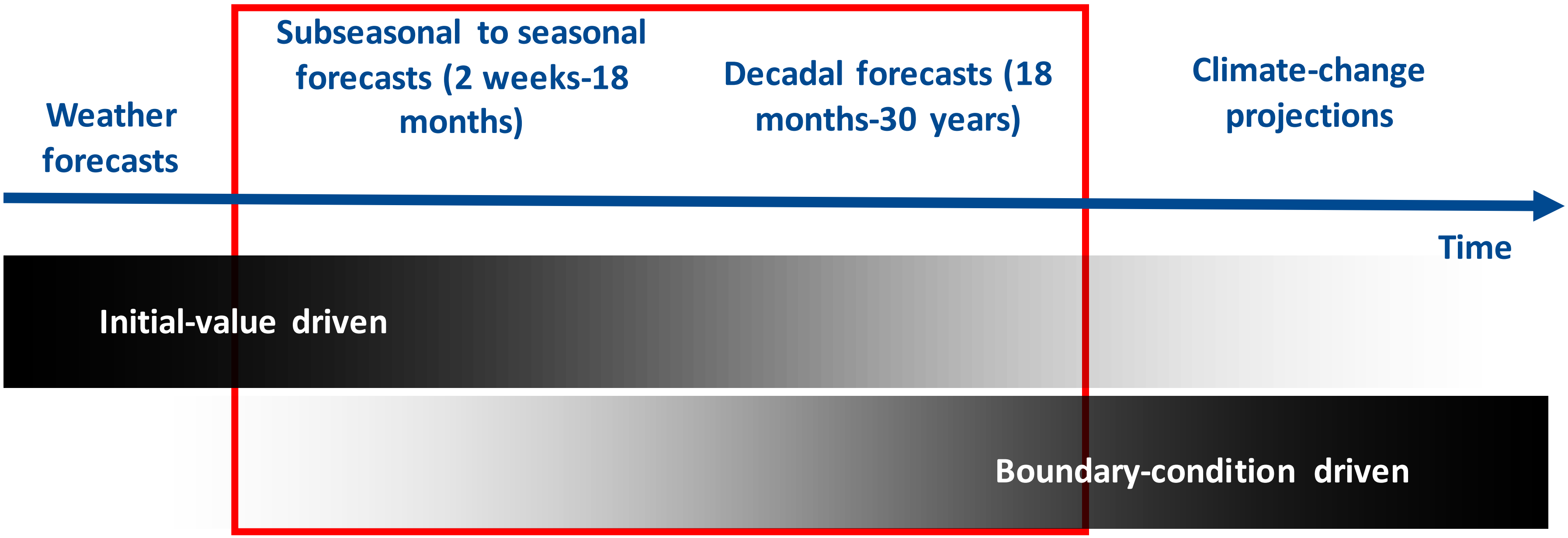
Prototypical climate service for energy



S2S4E
Climate Services for Clean Energy

Climate prediction: time scales

Progression from initial-value problems with weather forecasting at one end and multi-decadal to century projections as a forced boundary condition problem at the other, with climate prediction (sub-seasonal, seasonal and decadal) in the middle. Prediction involves initialization and systematic comparison with a simultaneous reference.



Adapted from Meehl et al. (2009)

Climate prediction experiments

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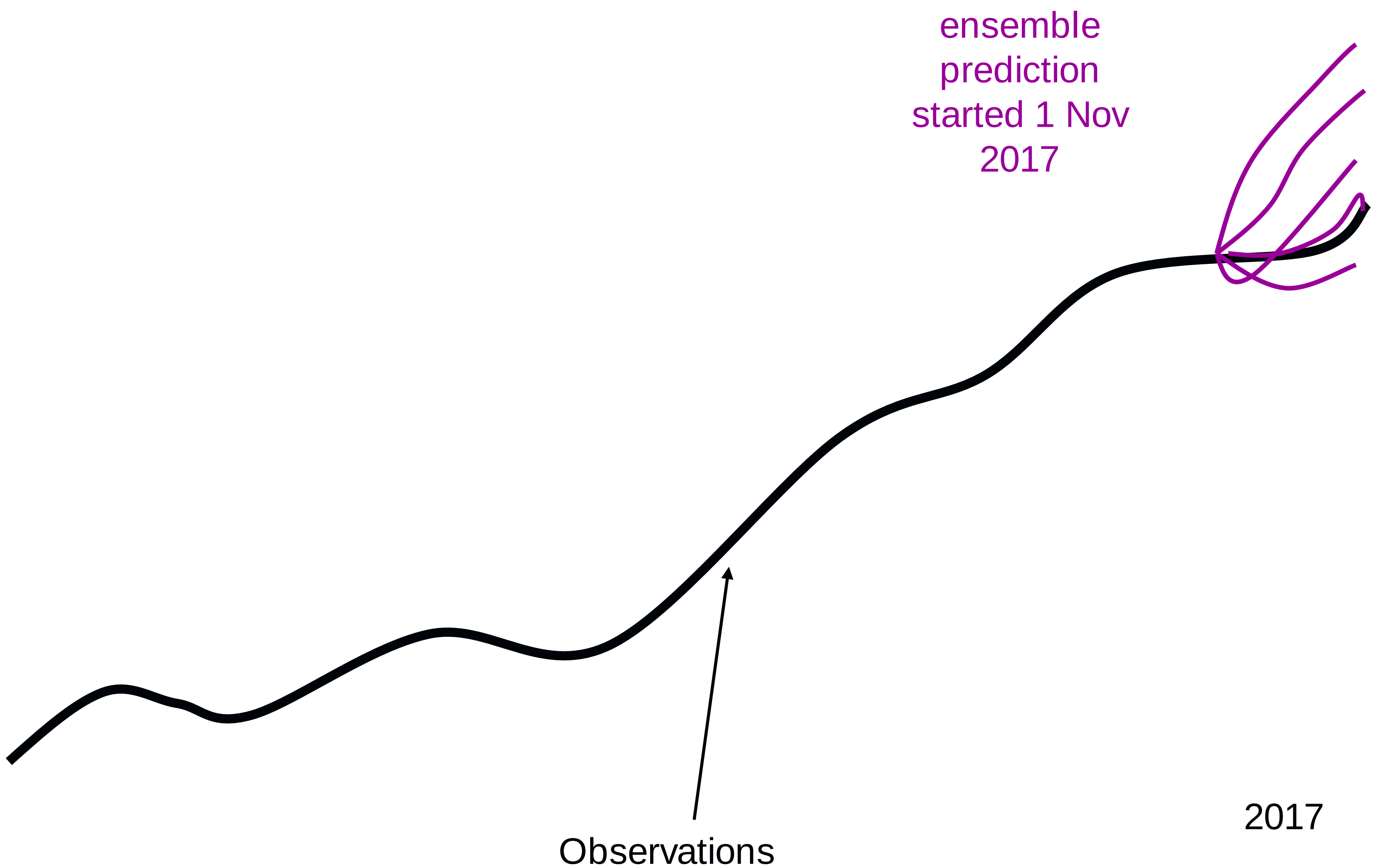
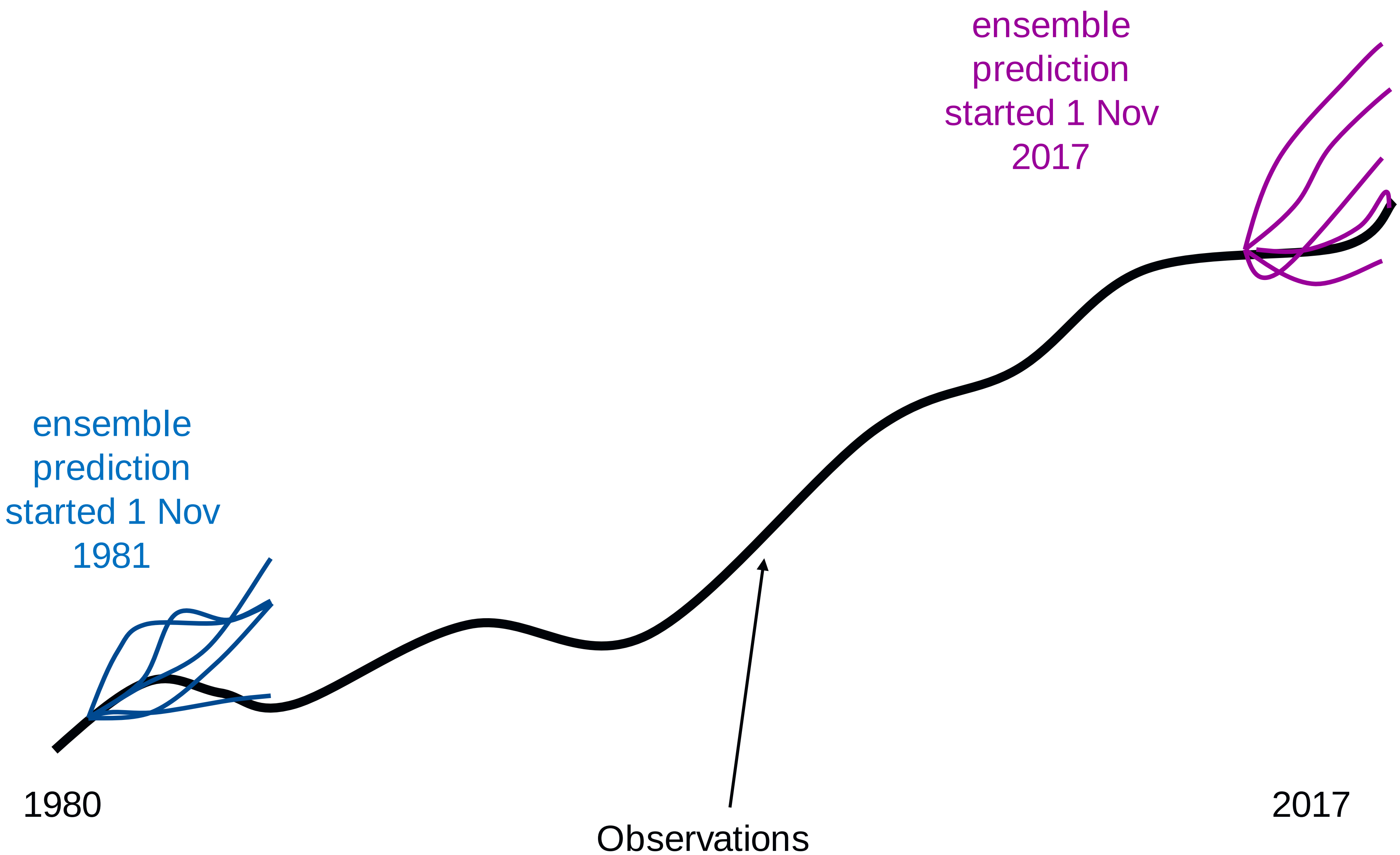
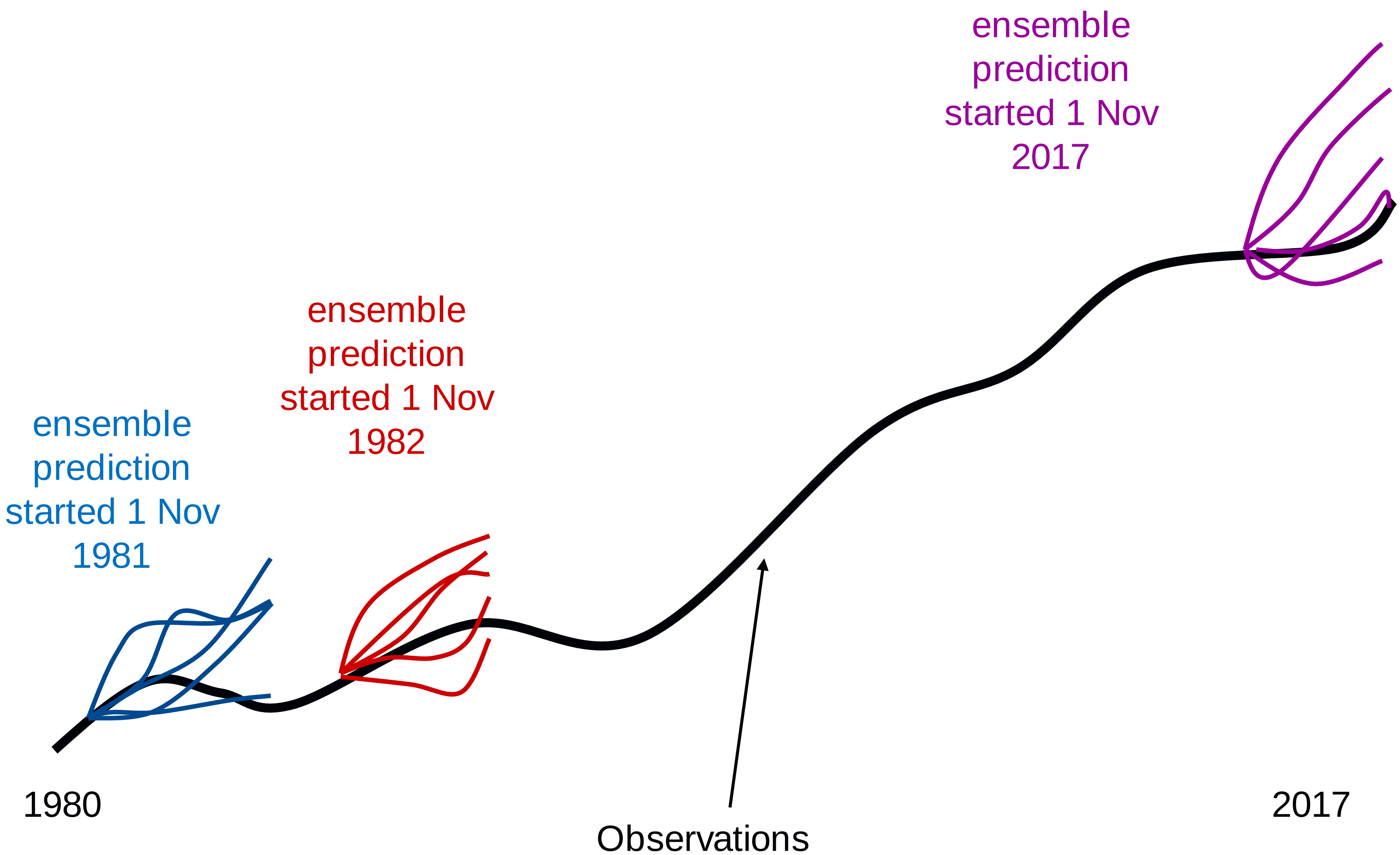


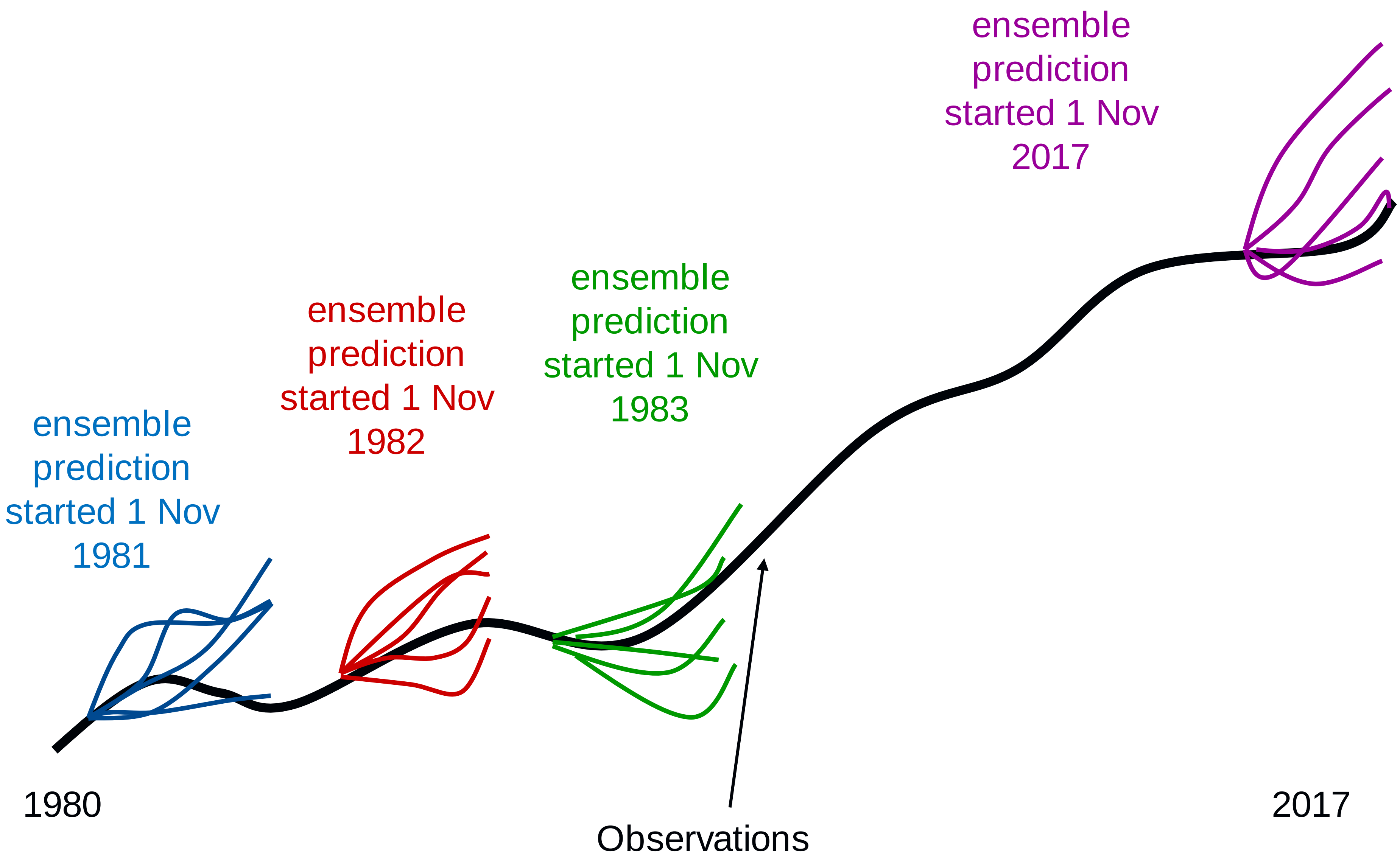
Climate prediction experiments



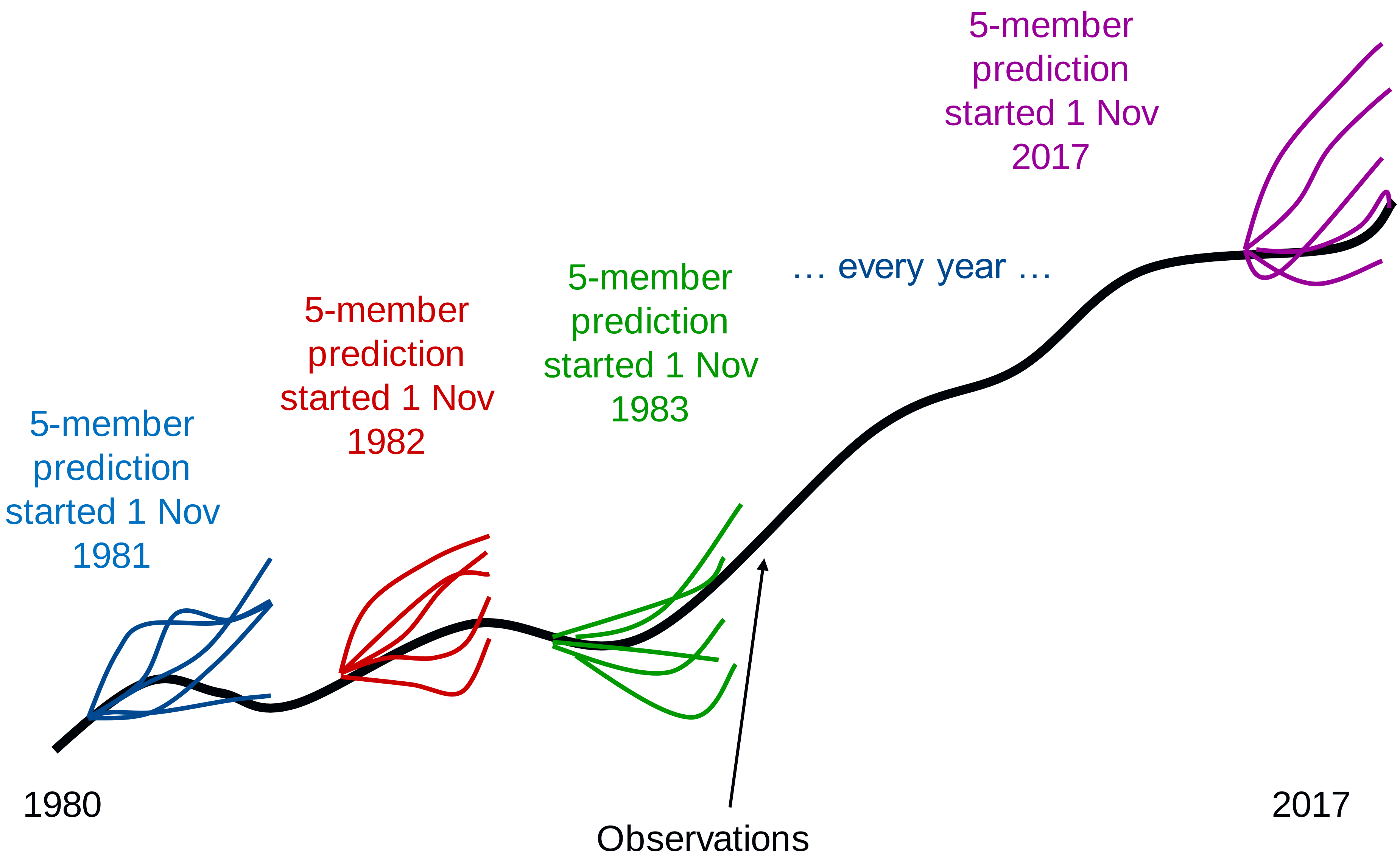
Climate prediction experiments



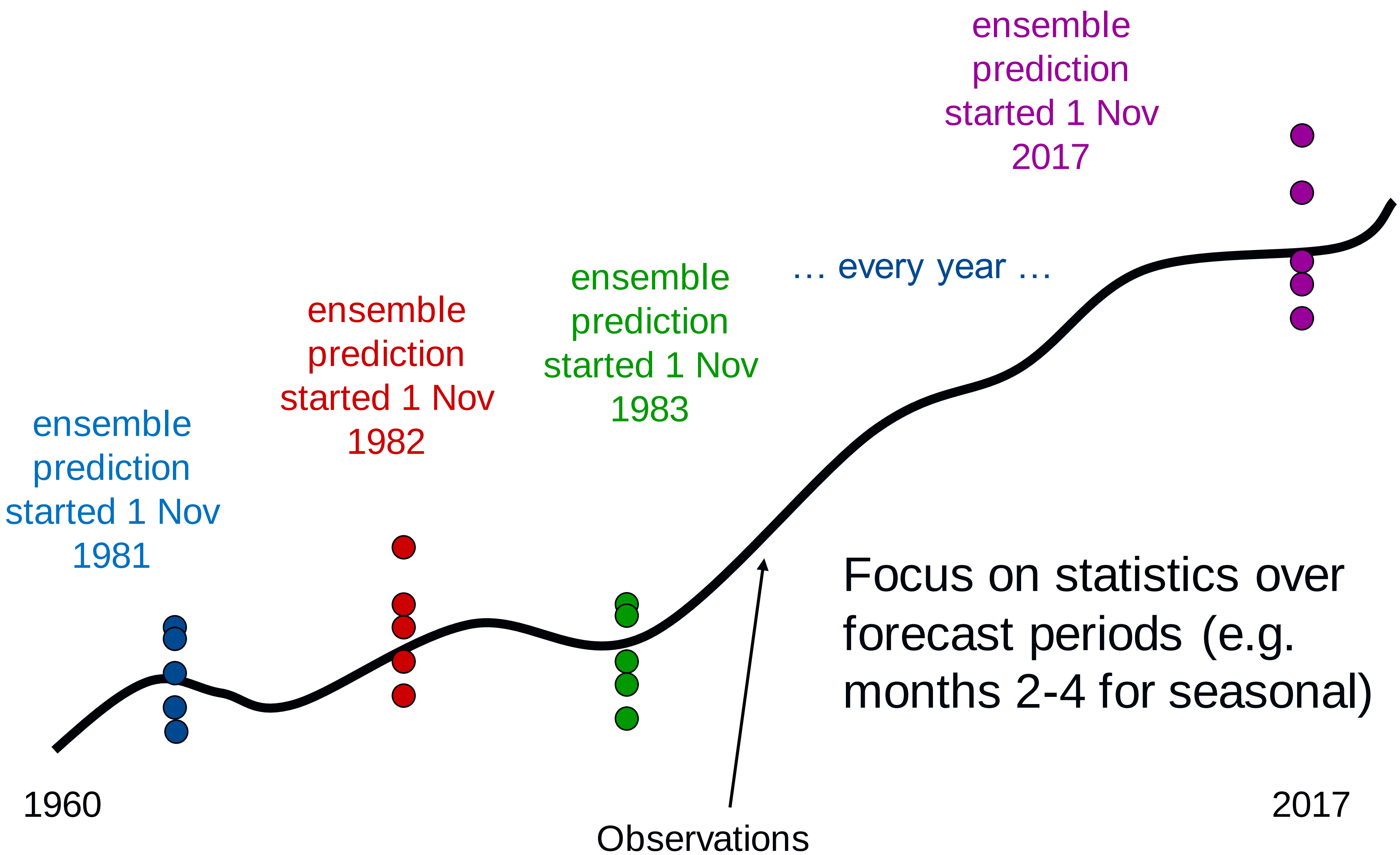
Climate prediction experiments



Climate prediction experiments



Climate prediction experiments



Focus on statistics over forecast periods (e.g. months 2-4 for seasonal)

Bias adjustment of forecasts

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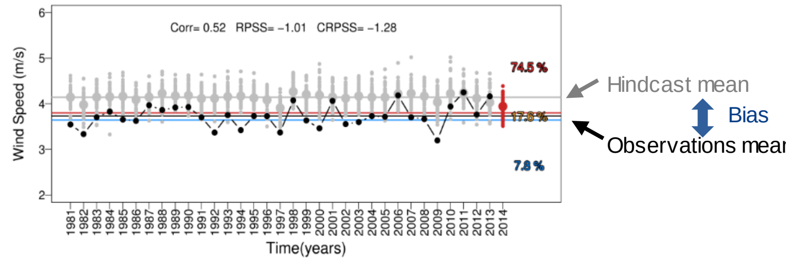
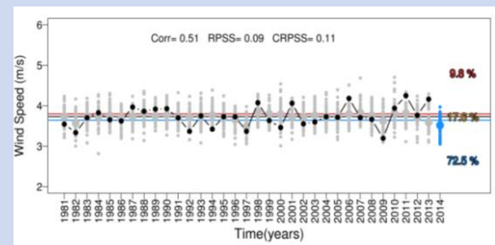
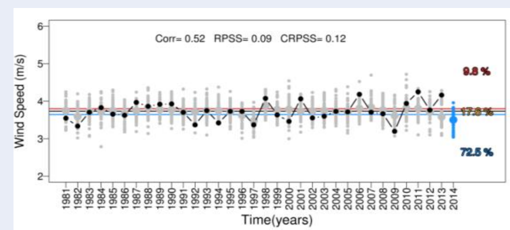
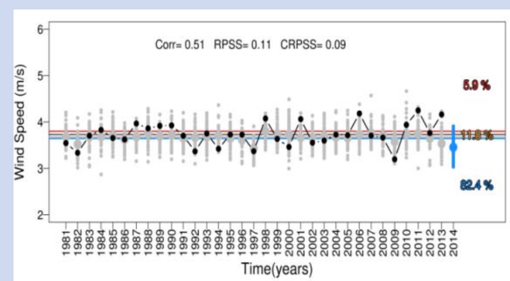
Raw data



Method	Equation	Description	Result
Simple bias correction	$$y_{j,i} = (x_{ij} - \bar{x})\frac{\sigma_{ref}}{\sigma e} - \bar{o}$$	Based on the assumption that both the reference and forecasted distribution are well approximated by a Gaussian distribution.	
Correlation -conserving calibration	$$y_{j,i} = \alpha x_i + \beta z_{ij}$$	Variance inflation modifies the predictions to have the same interannual variance as the reference dataset and corrects the ensemble spread to improve the reliability.	
Quantile mapping	$$y_{j,i} = (ecdf^{ref})^{-1}\, ecdf^{mod}(x_{ij})$$	It determines for each forecast to which quantile of the forecast climatology it corresponds, and then they are mapped to the corresponding quantile of the observational climatology.	

Impact of bias adjustment on forecasts

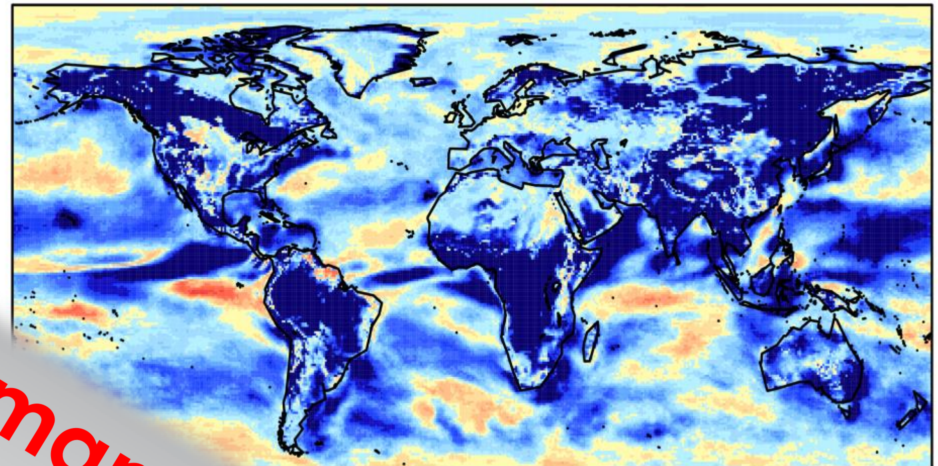
Ranked Probability Skill Score

$RPS = \frac{1}{M-1}\sum^{M} \left[\ldots \right]^2$

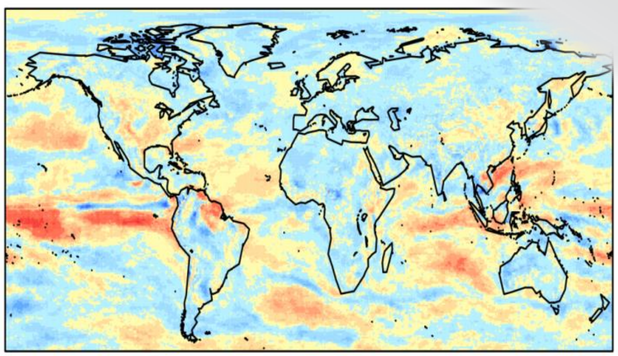
$RPSS = \ldots$

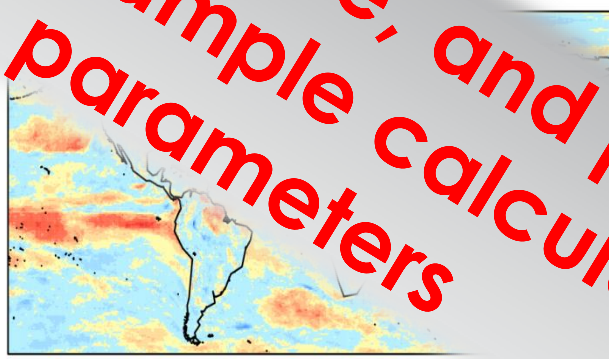
Similar performance, and penalisation by the off-sample calculation of parameters

Uncorrected

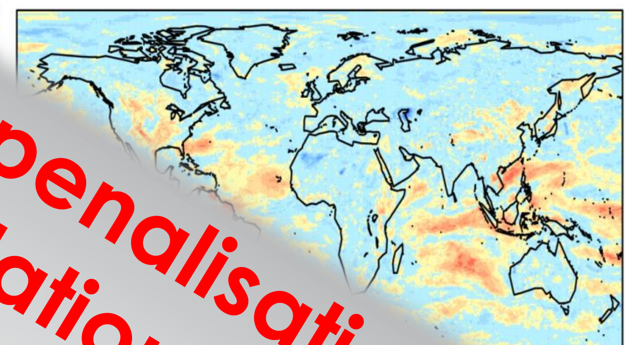


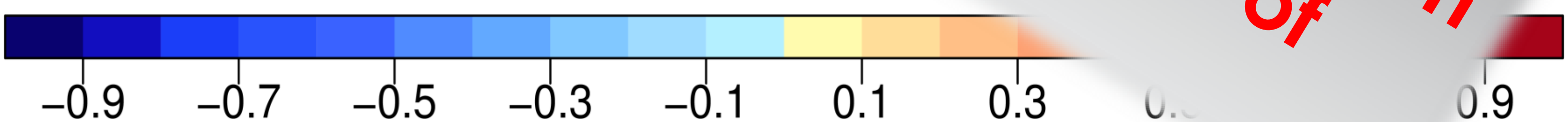
Simple





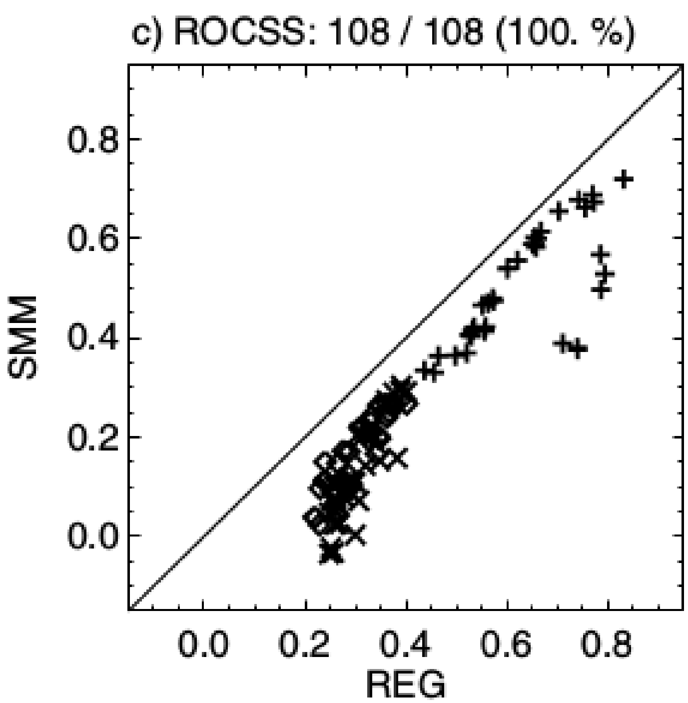
Q-Q mapping

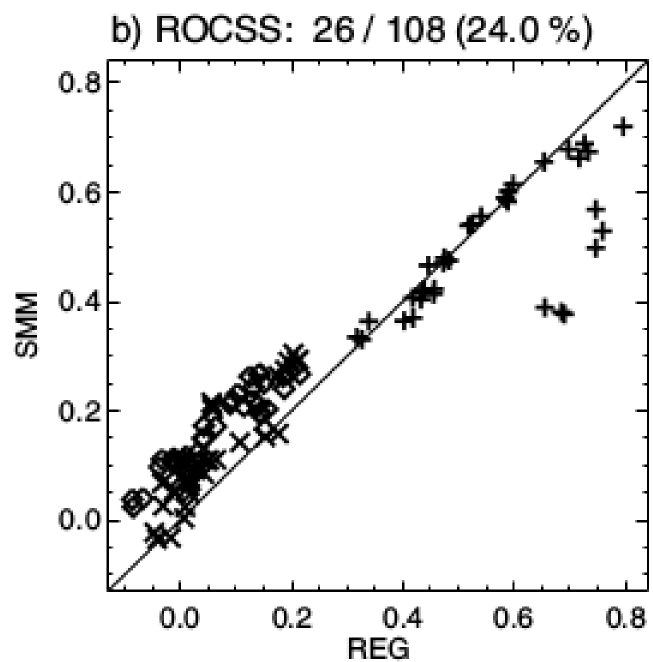




Impact of bias adjustment on forecasts

ROC skill score for a number of single multi-model (SMM) and adjusted through multiple linear regression (REG) forecasts from the ENSEMBLES experiment with (right) and without (left) cross-validation. Three variables, two start dates, two seasonal lead times, three regions and three events are used, with a symbol for each case.





Doblas-Reyes et al. (2005, Tellus A)

Reconstruction of wind forecasts

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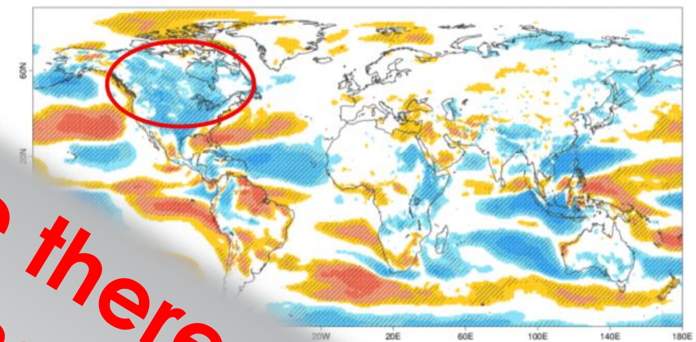
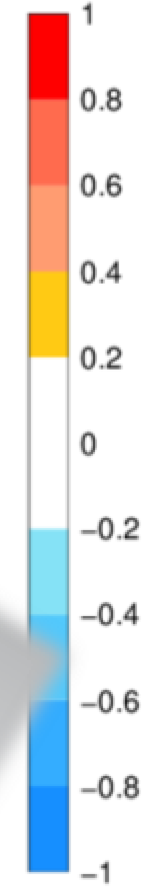
ECMWF S4 10-metre wind speed forecasts for DJF corrected with the predicted N 3.4 index on a regression estimated using ERA-Interim.

This works because there are biases in the teleconnections; it's the kind of information exploited in statistical downscaling

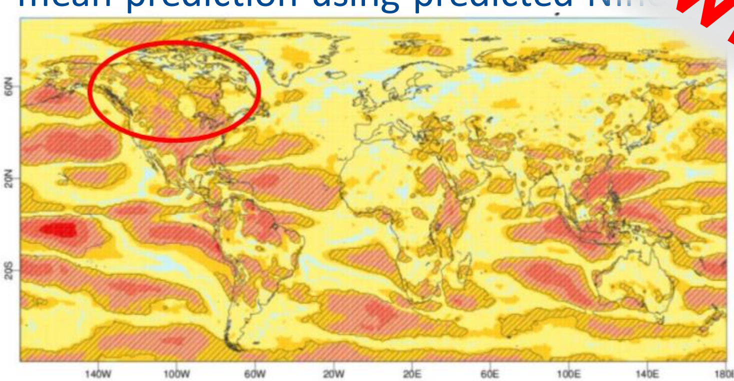
Correlatio ensemble- me 5)

Point correlation of Niño3.4 and 10-metre wind speed from ERA Interim





Correlation of the ECMWF S4 e mean prediction using predicted Ni



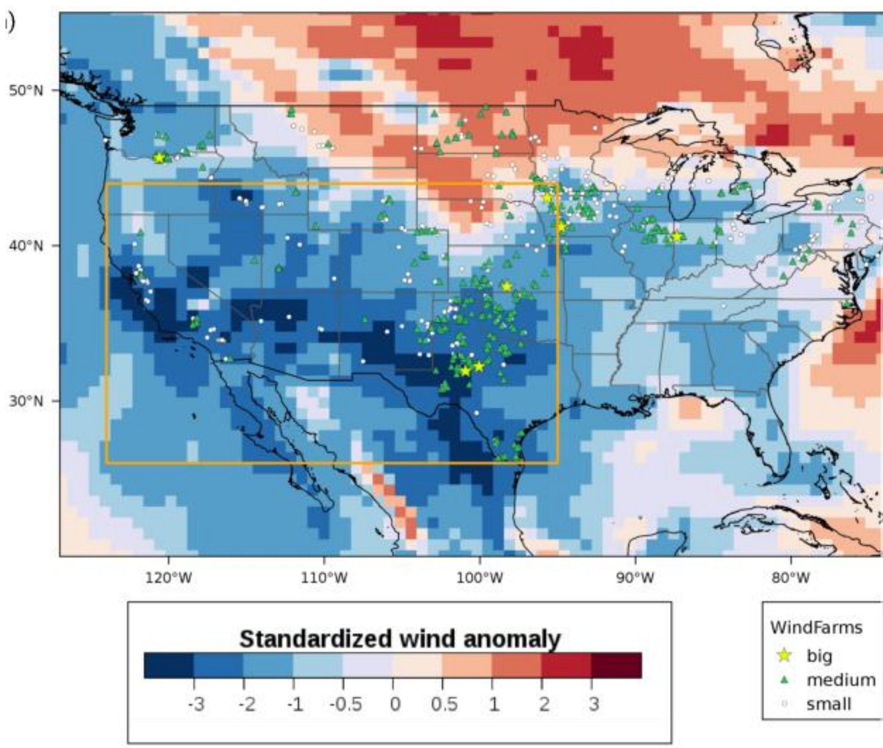
Niño3.4 and 10- ECMWF S4

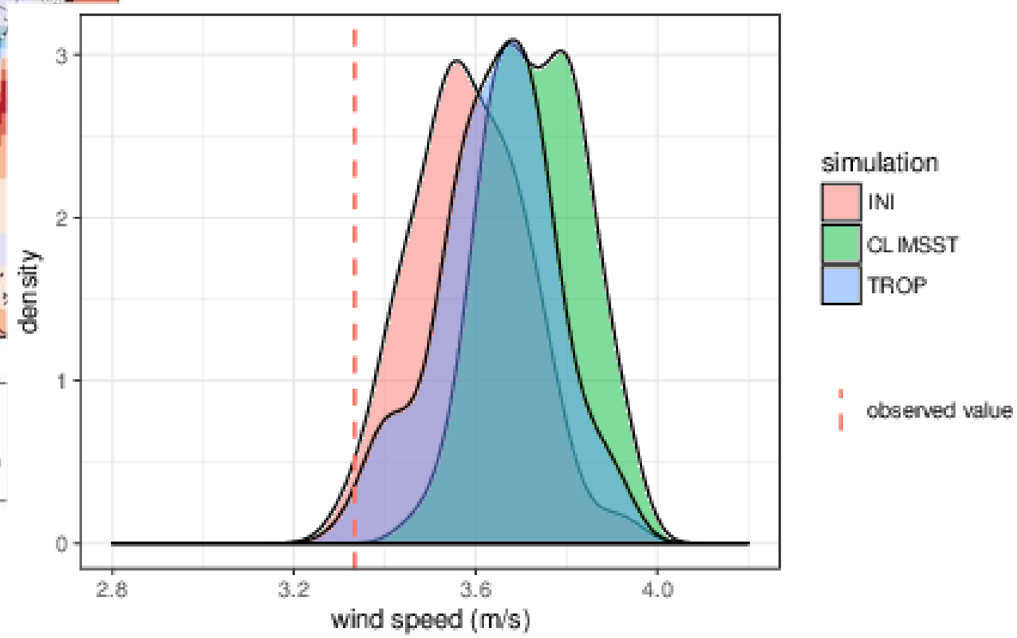
González et al. (in prep.)

Through the looking glass: D&A

Attribution of the JFM 2015 wind drought over North America. Both west tropical and extratropical Pacific SSTs play a role in the wind drought.

Shouldn’t have been for a wind-energy manager’s request, we’d never have looked into this issue





Lledó et al. (2018, JGR)

Through the looking glass: D&A

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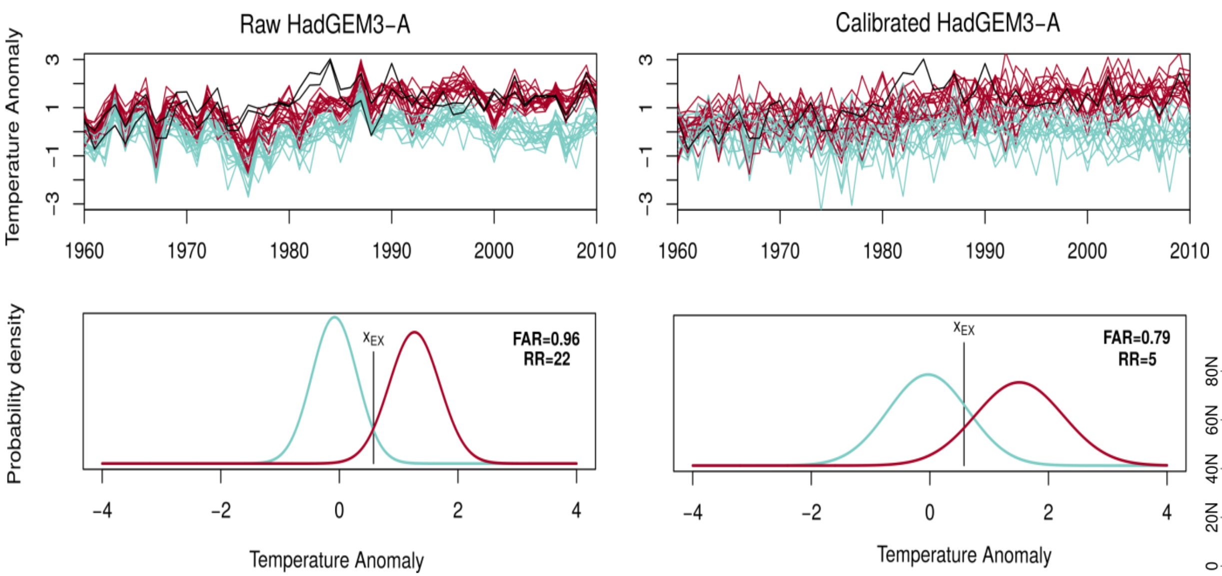
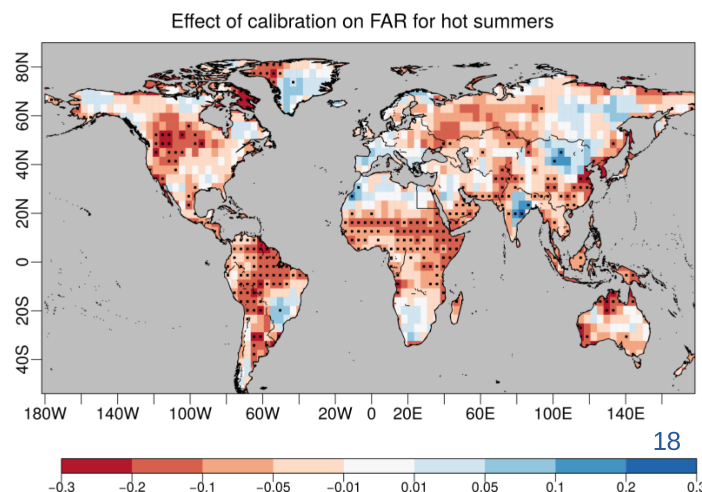
Effect of calibration on the attribution for warm (one in five years) summers at a grid-point in Sudan (12.6ºN, 34.4ºW).

Top panels show the observed temperatures (black, two datasets) and the UK quasi-operational attribution system (HadGEM3-A) considering all forcings (red) and only natural forcings (blue) with respect to the present-day climatology (1981-2010) derived from the all forcings ensemble. FAR and RR stand for fraction of attributable risk and risk ratio.



$$y = \alpha x_{EM} + \beta x'_{EM} + \gamma x_{TR}$$



Bellprat et al. (submitted)

Observational reference uncertainty

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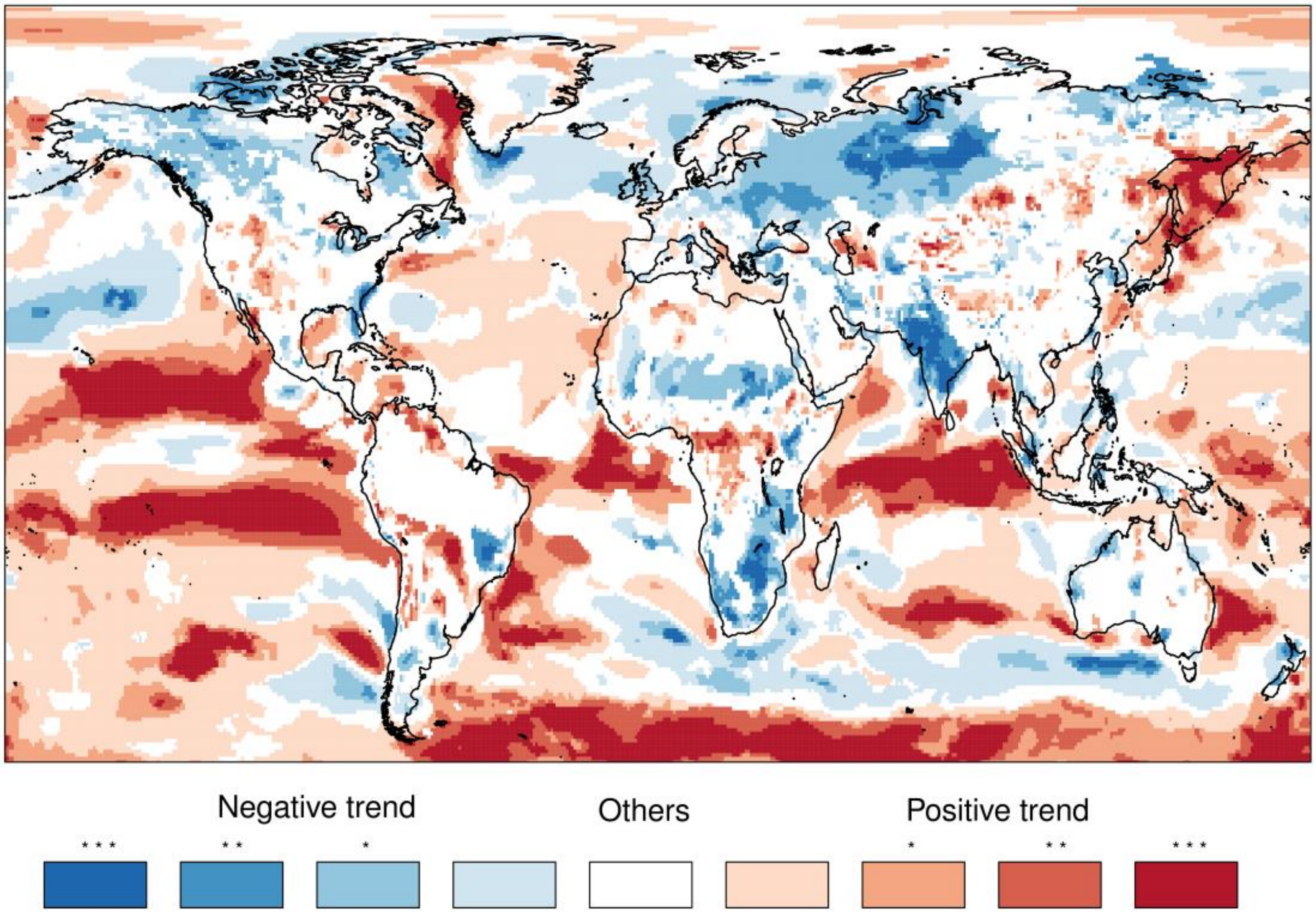
Coherence of the 10-metre wind speed trends in three reanalyses (ERA-Interim, JRA-55 and MERRA) over 1981-2015 during boreal winter.



Torralba et al. (2017, ERL)

Drift and systematic error

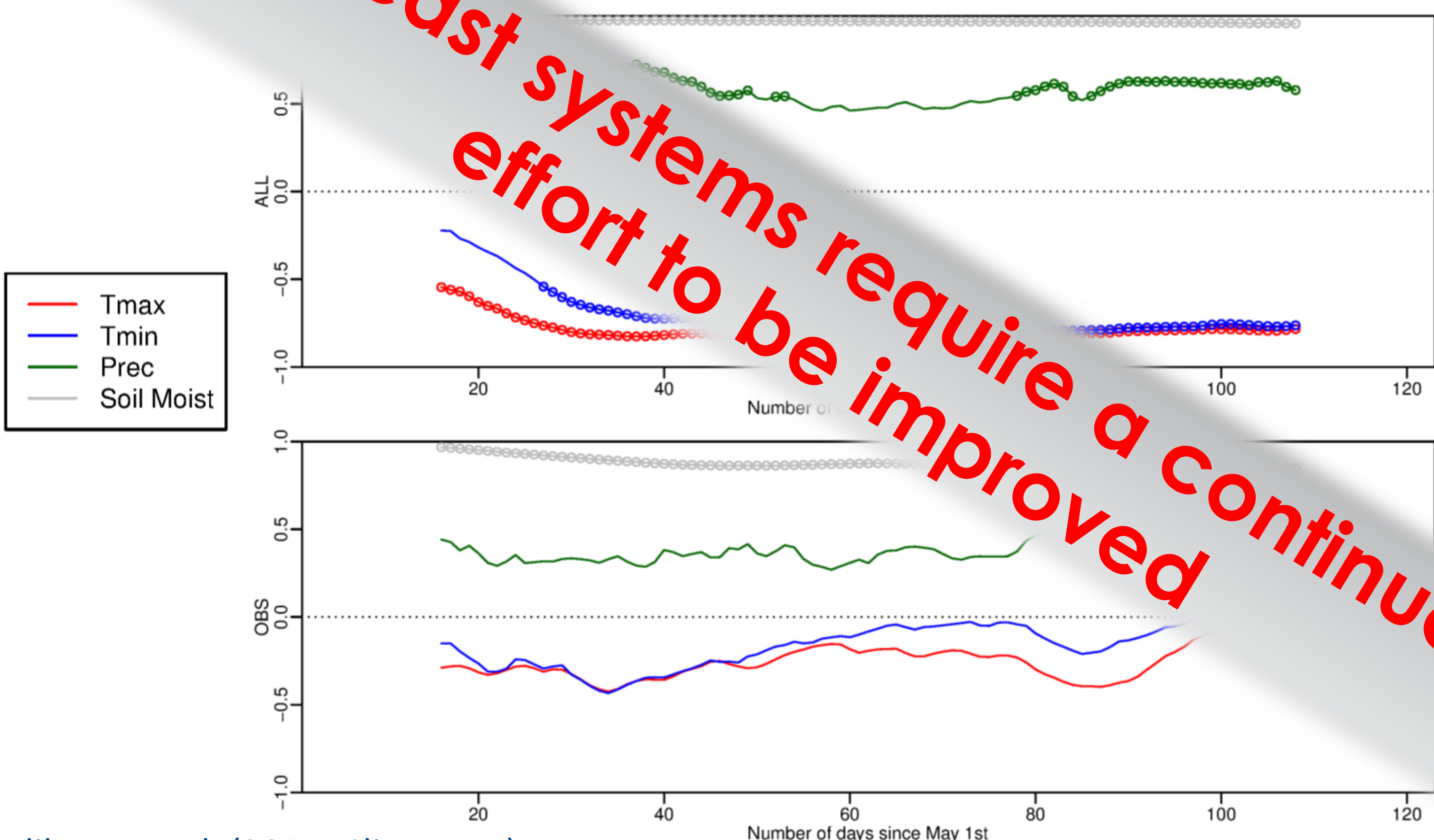
- In a climate forecast the model climatology is different for each start date because the model drifts from the initial conditions based on observations towards the model stationary climate.
- In this context, systematic errors are a moving target. The stationary systematic errors (those analysed in the CMIP exercises) are not necessarily relevant for climate predictions.
- The characteristics of the drift depend on the variable considered and can be either very fast (SLP, days) or very slow (ocean salinity, decades).
- The drift can be very informative when interpreting certain forecasts.

Systematic error destroys the skill

Correlation between 1st of May total soil water content and 31-day running mean of variables from the SPECS multi-model seasonal forecast (top) and ERAInt (bottom) over North American Great Plains.

The m… quickly to excessive land-atmosphere coupling

Forecast systems require a continuous effort to be improved



Ardilouze et al. (2017, Clim. Dyn.)

Working hand-in-hand with the users

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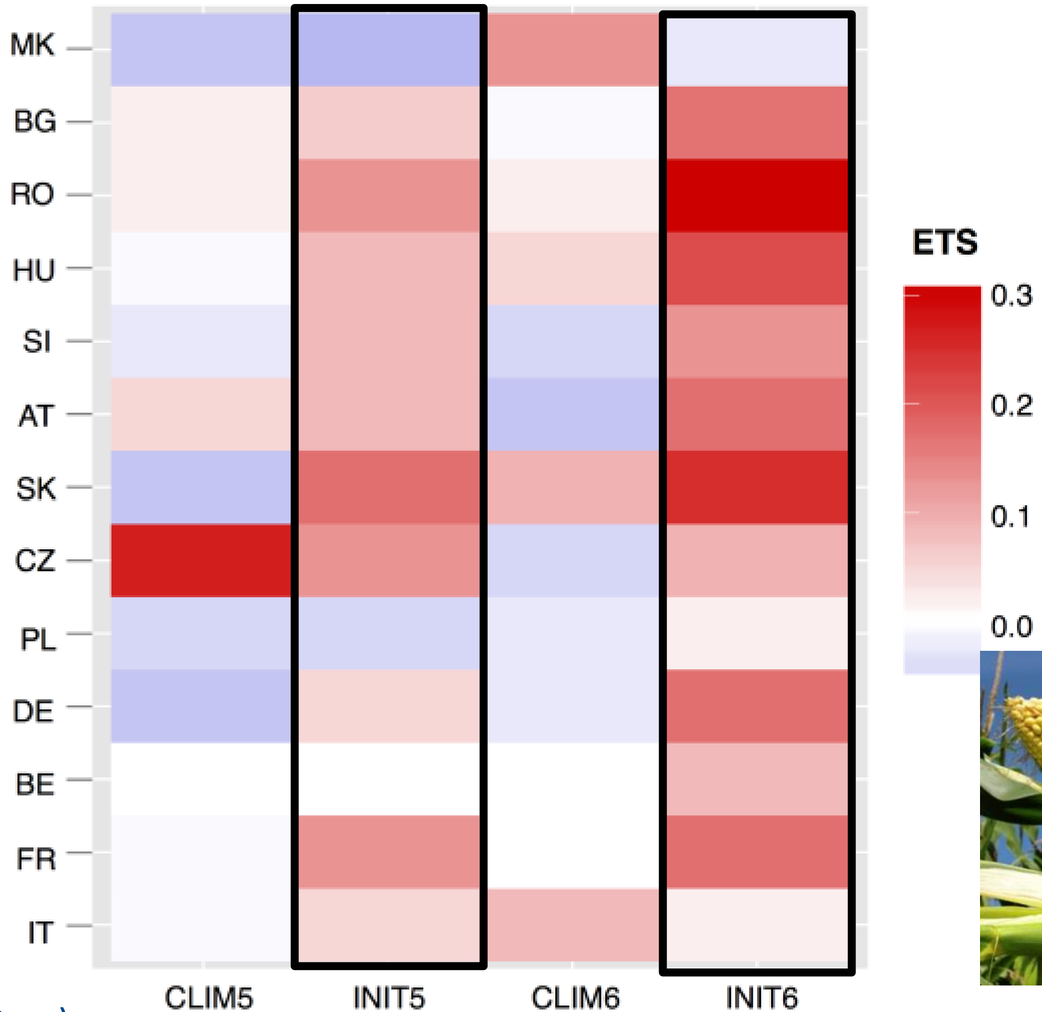
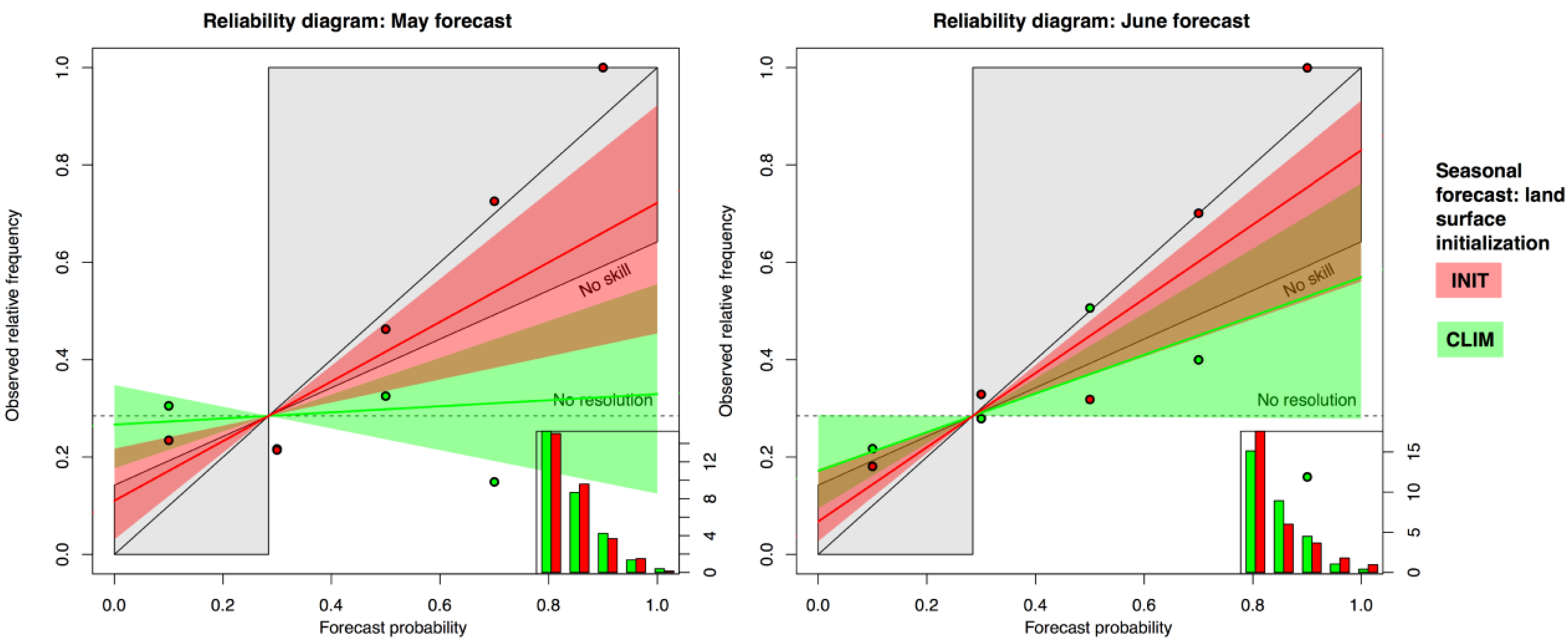
Equitable threat score (ETS) of predictions of poor maize yield (lower quartile) from EC-Earth when the land-surface uses realistic initial conditions (INIT) wrt conditions with no interannual information (CLIM).



Ceglar et al. (2018, Sci. Rep.)

Reliability diagram of predictions of poor maize yield (lower quartile) from EC-Earth seasonal predictions when land-surface is initialised with realistic (INIT) and climatological (CLIM) initial conditions with May and June start dates.



Ceglar et al. (2018, Sci. Rep.)

Summary

Bias adjustment is a central element of climate service development

- **User engagement**: not all users need bias adjustment (or downscaling), but many do, and their needs have to be identified.
- **Methodology generalisation**: bias adjustment, downscaling, calibration are concepts required wherever models are used.
- **System improvement**: bias adjustment can only improve if the forecast systems improve, which requires investment and feedback.
- **Heterogeneity**: link to and merge climate forecast data with communities with larger impact (urban, arts, social).
- **Education**: in the era of open data, take advantage of the open education opportunities.